1. REPORT DATE 01-31-2012	**2. REPORT TYPE** Final Report	**3. DATES COVERED** *(2/1/2009 - 12/31/2011)*

4. TITLE AND SUBTITLE
Noise Enhanced Sensory Signal Processing

5a. CONTRACT NUMBER

5b. GRANT NUMBER
[illegible]

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Pramod K. Varshney

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Syracuse University
113 Bowne Hall
Syracuse, NY 13244

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Air Force Office of
Scientific Research
875 N Randolph St, Arlington, VA 22203

10. SPONSOR/MONITOR'S ACRONYM(S)
[illegible]

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
AFRL-OSR-VA-TR-2012-0949

12. DISTRIBUTION / AVAILABILITY STATEMENT

DISTRIBUTION A: APPROVED FOR PUBLIC RELEASE

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Understanding and emulating sensory information systems is a challenging task. The goal of this project was to develop the theory of noise enhanced signal processing (NESP) where *the performance of some nonlinear systems may be enhanced by adding a suitable amount of noise to the input signal*. The main objective of this project was to explore the applicability of NESP based approaches to enhance the performance of ``source blind'' signal processing algorithms. During this effort, we have explored the NESP mechanism for signal detection and estimation problems in a non-stationary and dynamic environment and developed some iterative learning algorithms to apply NESP based procedure with incomplete knowledge. We investigated image enhancement algorithms based on stochastic resonance (SR) noise which improve the performance of suboptimal image enhancers. We further explored the recently developed *Compressive Sensing* based measurement scheme in performing detection, classification and estimation with sparse signals and derived achievable performance limits. Results obtained have been documented in a number of technical publications.

15. SUBJECT TERMS
Noise Enhanced Signal Processing, Image Processing, Stochastic Resonance, Compressive Sensing, Dithering

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Pramod [illegible] Varsh[illegible]
Unclassified	Unclassified	Unclassified	None	18	**19b. TELEPHONE NUMBER** *(include area code)* [illegible]

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

Final Report

AFOSR Project:

Noise Enhanced Sensory Signal Processing

Syracuse University
Syracuse, NY 13244

Reporting Date: 02/01/2009-12/31/2011

Project #: FA9550-09-1-0064

Principal Investigator: Prof. Pramod K. Varshney
Department of EECS, Syracuse University

2. Objectives

The overall objective for this project was to design, implement and test efficient NESP based theories and algorithms to enhance the performance of sensory signal and image processing systems in various environments. This also included the investigation of the use of random projections on measurements in sparse signal processing, which is termed as Compressive Sensing (CS). These required progress towards the following objectives:

- Address fundamental issues such as improvability conditions for signal processing systems and bounds on achievable performance;
- Explore the NESP mechanism for signal detection and estimation problems in a non-stationary and dynamic environment;
- Algorithms for learning the changing nature of data sources;
- Application of NESP for sensory signal processing tasks such as voice activity detection, blind source separation, and image enhancement;
- Understand the neural processing of the ear in an attempt to determine how noise enhancement might improve hearing. A further goal was to apply what has been learned to improve current techniques of signal processing by leveraging the ear's ability to process signals;
- Explore the use of CS mechanism and develop efficient algorithms for sparse signal detection and classification with different signal and sparsity models; and
- Explore the effect of quantization and channel impairments in communication on sparse signal processing based on CS-based measurements.

3. Research Efforts *(200 word summary)*

We developed NESP theory for noise enhanced nonparametric detection where we investigated the detection performance of *additive noise modified nonparametric detectors* and the optimal noise was determined for both Sign and Dead-Zone limited detectors. We also considered the *nonparametric distributed estimation problem* for a parallel distributed estimation system and a set of nonparametric one-bit quantizers were proposed. *Noise-Refined Image Enhancement Using Multi-Objective Optimization (MOO)* was investigated where we developed an image enhancement system based on stochastic resonance (SR) noise, for improving the suboptimal image enhancers. We investigated the image segmentation problem by incorporating the human visual system (HVS) properties, to achieve the segmentation results which are preferred by the humans. Further, we investigated the effect of stochastic resonance in speech signal processing. A new Approach to Fourier Synthesis with Application to Neural Encoding and Speech Classification was proposed. With the Poisson Spectral Representation for Random Process Modeling, we have been able to show that noise can enhance the neural firings. In the context of CS, we investigated the performance limits of detection and classification of sparse signals with compressive measurements. We found sufficient conditions which ensure the reliable recovery of support of sparse signals from *quantized* compressive measurements in the presence of noise.

4. Summary of Accomplishments/New Findings

Noise Enhanced Nonparametric Detectors

Nonparametric detectors are widely used in signal detection problems and provide a guaranteed level and reasonable power for large classes of input distributions. When nonparametric detectors are designed, the underlying distributions are assumed unknown except that certain properties such as symmetry are assumed. In most cases, a nonparametric detector is less efficient than the optimal detector. Therefore, it is a very interesting and important problem to try to improve the detection performance of a nonparametric detection scheme while maintaining its constant false alarm rate (CFAR) property.

In this work, we investigated the effect of adding noise to nonparametric detectors. The detectors are assumed fixed nonparametric detectors such that we cannot adjust their parameters or the thresholds, and the underlying distributions for both hypotheses are assumed to be known when we design our noise modified nonparametric detectors. Three typical nonparametric detectors were examined, namely, the sign detector, the Wilcoxon detector and the dead-zone limiter detector (DZLD) as they are the well-known sign, rank and conditional tests, respectively. The optimal noise distribution is determined. For the case where only unlabeled data are available, a simple and robust adaptive learning algorithm is proposed to estimate the optimal additive noise distribution. A near optimal performance is reached very quickly and accurately.

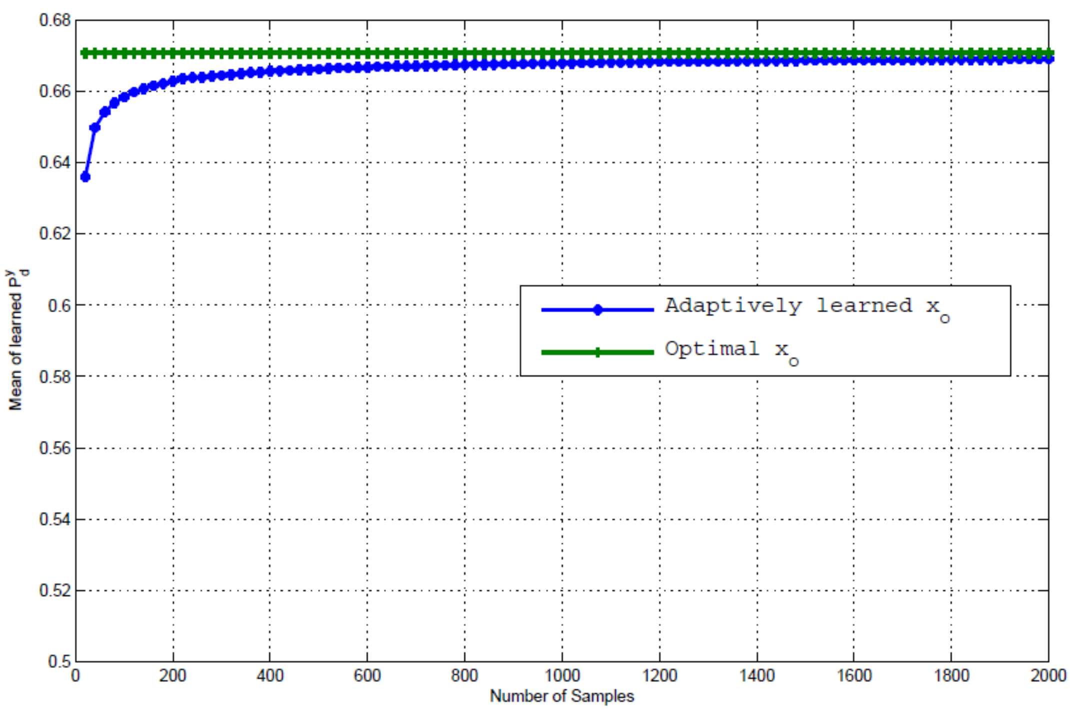


Fig.1. Performance of the adaptive noise enhanced nonparametric detectors based on the proposed learning algorithm. The algorithm converges to the global optimal rapidly as the number of samples increases.

.

Achieving Distributed Estimation Performance via a Dithering Noise

Parameter estimation from quantized data, especially from one-bit quantized samples has long been an important active research area. Among a number of distributed estimation system models, the parallel model consisting of a fusion center and local sensors communicating with the fusion center directly is the most widely used and studied one.

Full precision Cramér-Rao lower bound (CRLB) where no quantization is assumed is often employed to evaluate and compare distributed estimation performance where the sensor observations have to be quantized before any further processing. However, as it completely disregards quantization and often does not exist when the sensor observation noise is bounded, as an evaluation metric, full precision CRLB is often too optimistic or not applicable.

In this work, we considered the performance evaluation problem for distributed estimation systems with identical one-bit quantizers under the minimax CRLB criterion. We first established the sufficient conditions for the optimal pair of noise distribution and the quantization rule. The performance limit is determined by finding the optimized quantizer under the perfect observation model where the sensor observations are noiseless. When the sensor noise does exist, the set of optimal noise distribution function and quantizer are also determined. Compared to the full precision CRLB, the performance limit is shown to be a much tighter bound when the parameter range is relatively large. Effectiveness of the optimal Gaussian noise, Uniform and the sinusoid noise are evaluated and the optimality of the proposed quantization scheme was demonstrated.

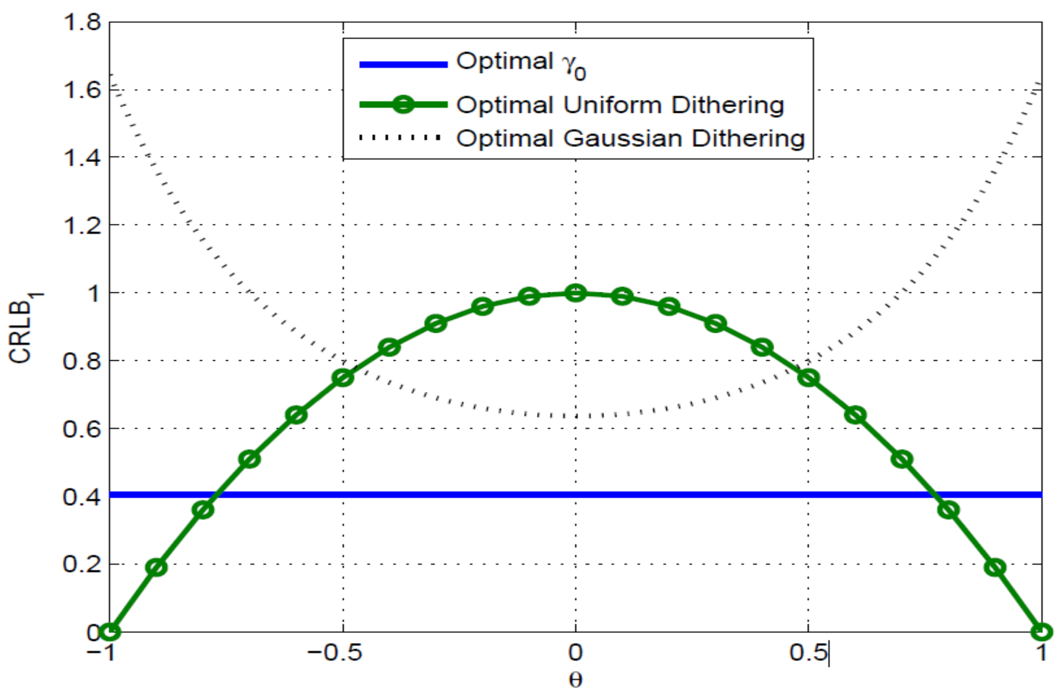


Fig.2 Performance comparison of distributed estimation systems in terms of CRLB for the optimal Gaussian, uniform and Sinusoid dithering noises; minimax criterion is adopted for the system design: lower maximum CRLB means better estimation performance.

Optimal Noise Enhanced Distributed Estimation with Incomplete Information

In practical applications, the *exact information about the observation model* is often unknown. In this work, we considered the nonparametric distributed estimation problem where the local sensor observation noises are assumed to be bounded with known first N moments but with *unknown probability density functions* (pdf). For the ease of discussion, in this work, we mainly considered *the special case when all the first N noise moments as well as the sensor quantization rules are assumed to be the same for all sensors*. The actual sensor observation noise distributions, however, *do not have to be identical or independent*. Moreover, the distributed estimators we develop can be generalized straightforwardly for the more general non-identical case. Once again, the nonparametric sensor quantization rules developed in this paper are assumed identical across the sensors even though the sensor noises may not be i.i.d. We first developed a set of nonparametric distributed estimators for the general case where N can be any positive integer. The proposed nonparametric estimators were shown to be either unbiased or at least asymptotically unbiased with a known estimation variance. The design problem where the sensor noises are independently distributed with known first moment or the first two moments, i.e., $N = 1$ or $N = 2$, was examined in detail. Moreover, we also evaluated the performance of the proposed estimation schemes when the sensor noises are not independent but m-dependent. The proposed nonparametric distributed quantization and estimation schemes are still consistent and the effect of the dependence was quantified. Performance of the distributed estimation schemes was also investigated for the case where the channels between sensors and the fusion center are noisy. The relationship between the proposed local quantizers and nonsubtractive dithering was explored. It was shown that *optimal quantization can be achieved by a deterministic quantizer with a dithering noise added to the observed signal*.

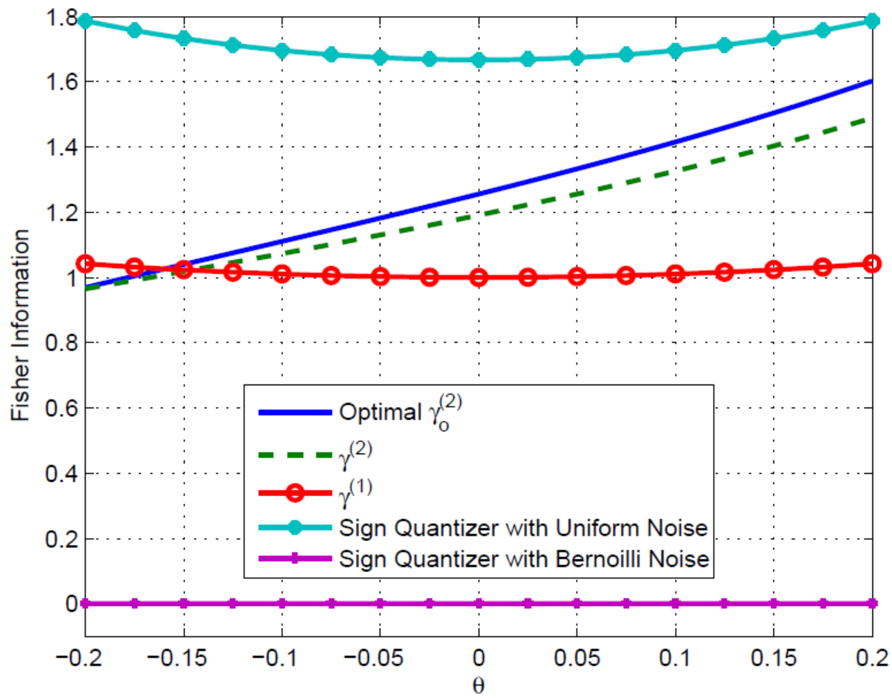


Fig3. Performance comparison of distributed estimation systems in terms of Fisher Information for the optimal nonparametric quantizers based on 1st and 2nd moment information; minimax criterion is adopted for the system design: higher minimum Fisher Information means better estimation performance.

Noise Enhanced Image Enhancement based on Multi-objective Optimization

Image enhancement plays a fundamentally important role in nearly all of the vision and image processing systems. In this work, we presented a novel scheme for the enhancement of images using stochastic resonance (SR) noise. In this scheme, a suitable dose of noise is added to the lower quality images such that the performance of suboptimal image enhancer is improved without altering its parameters. Image enhancement is modeled as a constrained multi-objective optimization (MOO) problem, with similarity and some desired image enhancement characteristic being the two objective functions. The principle of SR noise-refined image enhancement was analyzed, and an image enhancement system was developed. A genetic algorithm-based MOO technique was employed to find the optimum parameters of the SR noise distribution. In addition, a novel image quality evaluation metric based on human visual system (HVS) was developed as one of the objective functions to guide the MOO search procedure. For illustration, four types of SR noises were employed in this work to improve different enhancers. Encouraging results were obtained when applied to a number of image distortion situations.

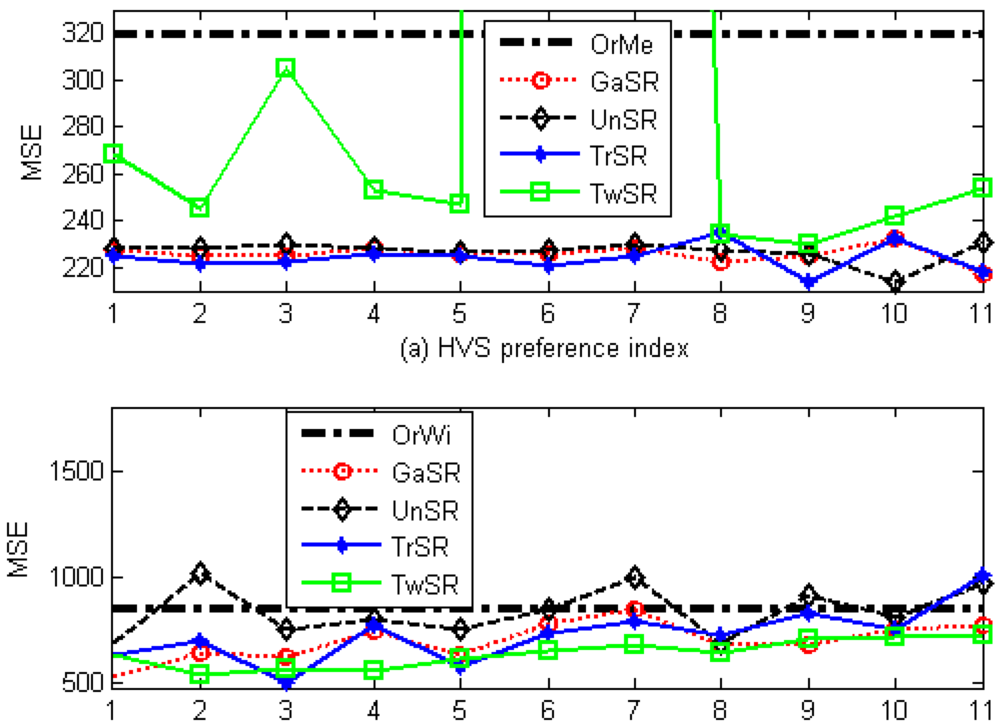


Fig.4. MSE of the de-noising results using median and Wiener filters. (a) Median filter-based de-noising; (b) Wiener filter-based de-noising. OrMe and OrWi mean the de-noising using original median and Wiener filter, respectively, without SR noise. Adding a suitable SR noise to the image prior to processing can significantly improve the performance.

Human Visual System-Driven Image Segmentation Algorithm

In most circumstances, humans are the ultimate judge of the quality of a segmentation result. Thus a segmentation algorithm is likely to yield satisfactory results if the objective function is designed by including human visual system (HVS) preferences within the context of segmentation. In this work, the maximum *a posteriori* probability-Markov random fields (MAP-MRF) framework was employed for the segmentation problem. More specifically, several HVS-based segmentation quality evaluation metrics were incorporated into the objective function as prior information, which were encoded in the MRF model to obtain the *a posteriori* probability distribution of the segmentation result given the observed image data, and the just-noticeable difference (JND) model was employed when calculating the difference of the image contents. Segmentation was carried out in an iterative manner, which aims at finding the MAP solution to the optimization problem. In the segmentation procedure, the “better” intermediate segmentation result, as evaluated by HVS based metrics for region and boundary, was assigned a higher survival probability. Experiments were carried out to compare the performances of the presented algorithm and several representative segmentation algorithms available in the literature, and very encouraging results were obtained.

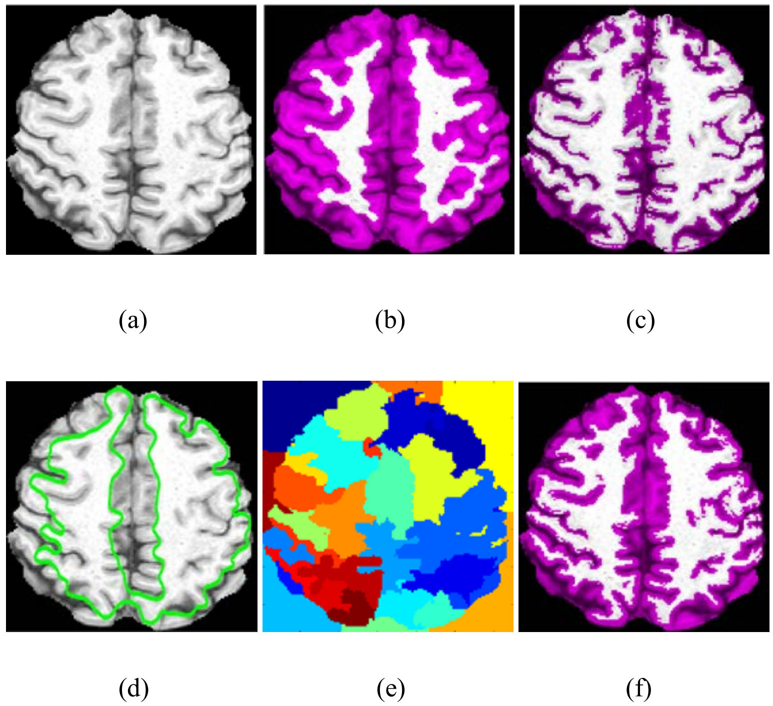


Fig.5. Original MRI brain image and the segmentation results. (a) Original MRI brain image; (b) segmentation by conventional MRF [1]; (c) segmentation by Otsu thresholding [2]; (d) segmentation by level set evolution-based method without reinitialization [3]; (e) segmentation by multi-scale normalized cuts-based segmentation [4]; (f) segmentation by the presented HVS-driven image segmentation algorithm. We wish to segment the white matter (WM) from the gray matter (GM) and cerebrospinal fluid (CSF). The segmented non-WM tissues are shown using purple and black colors in (b), (c) and (f). The regions enclosed by the light green curves in (d) correspond to the segmented WM. In (e), we expect the segmented WM to have the same color.

References

[1] S. Z. Li, *Markov Random Field Modeling in Computer Vision*. New York: Springer-Verlag, 2001.

[2] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Trans. on Sys., Man., Cyber, v*ol. 9, pp.62–66, 1979.

[3] C. Li, C. Xu, C. Gui, and M.D Fox, "Level set evolution without re-initialization: a new variational formulation," in *Proc. IEEE Computer Society Conference on Computer Vision and Patter Recognition (CVPR)*, vol. 1, pp. 430- 436, 2005.

[4] T. Cour, F. Benezit, and J. Shi, "Spectral segmentation with multi-scale graph decomposition," in *Proc. IEEE International Conference on Computer Vision and Pattern Recognition (CVPR),* 2005.

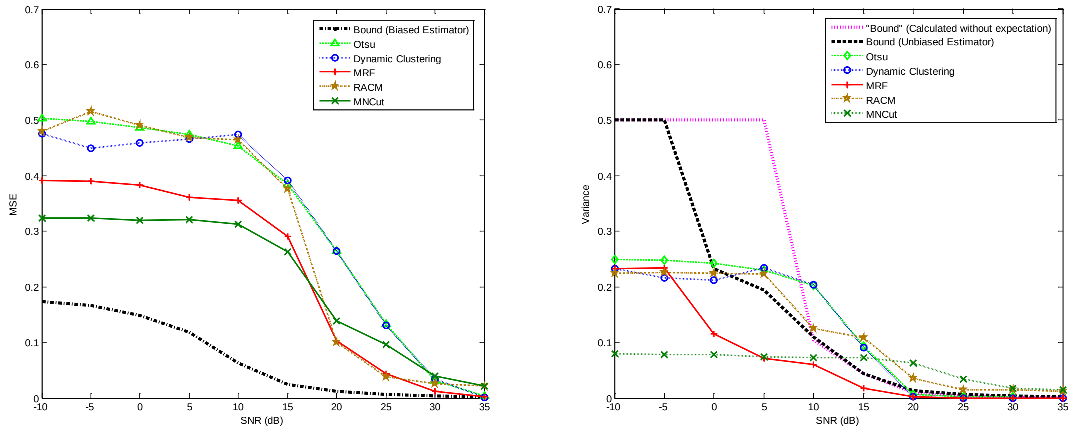
Performance Limits of Image Segmentation Algorithms

Image segmentation is a very important step in image analysis. Performance evaluation of segmentation algorithms plays a key role in both developing efficient algorithms and in selecting suitable methods for the given tasks. Although a number of publications have

appeared on segmentation methodology and segmentation performance evaluation, very little attention has been given to statistically bounding the performance of image segmentation algorithms. Therefore, an investigation of the performance bound, which is only associated with the available image data and is independent of the segmentation algorithms, is very helpful to evaluate the efficiency of image segmentation techniques. A tight performance bound can tell us what the best achievable performance of any image segmentation algorithm is for the specific image content. Thus, performance bounds can serve as benchmarks for the image dataset and segmentation algorithms. They can also be used to study how the image content or image preprocessing operations affect the segmentation performance. The distance or gap between the actual segmentation error of an approach and a tight bound can provide us with the efficiency of that segmentation approach and available room for improvement.

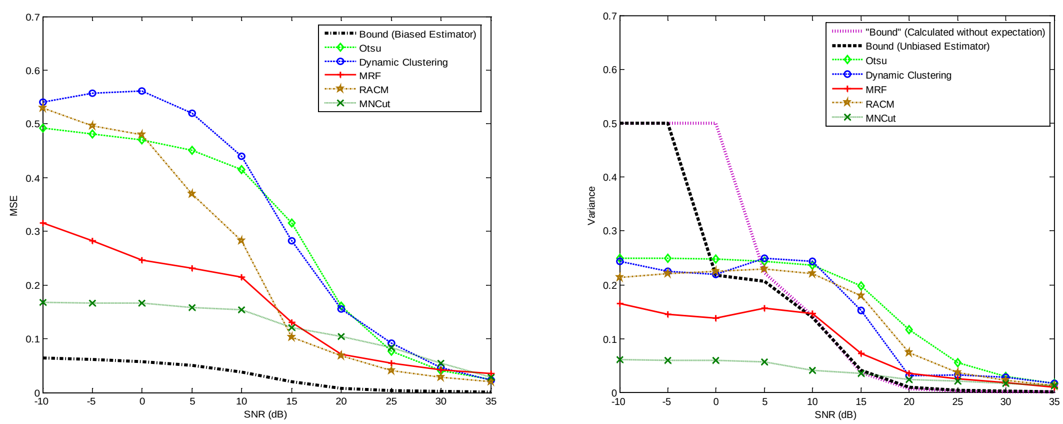
In this work, we formulated image segmentation as a statistical parameter estimation problem and derived Cramér–Rao bound (CRB) on the performance measure, namely on the mean square error (MSE) of the resulting pixel labels, based on the biased estimator assumption and Affine bias model. In addition, an approximation was made when computing the expectation of the inverse Fisher information matrix to reduce the computational burden. Bootstrapping technique and empirical approximation to the second-order statistics were employed to overcome the difficulty when the probability distribution of the images was unknown. Our final goal was to derive a tight performance bound for the image segmentation problem and compare the bound with the performance of various segmentation algorithms when applied to different image datasets. The effect of the factors, such as the intensity contrast in an image on the segmentation result, were investigated via the bound, which gave us insights into the achievable accuracy of a segmentation algorithm in segmenting a specific image.

Experimental results were obtained where the performance of several representative image segmentation algorithms was compared with the derived bound on both synthetic and real-world image data. From Figs. 6~8, it can be seen that the bounds derived from the biased estimator assumption bounded the performance of the segmentation algorithms from the bottom, but those derived from the unbiased assumption failed.



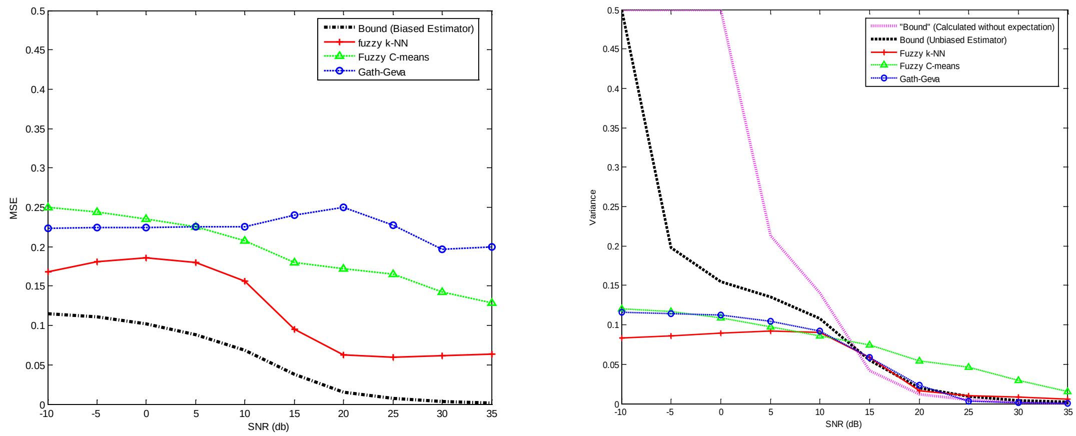
(a) (b)

Fig. 6 Bounds for hard image segmentation (a synthetic image), RACM: Region-based active contour model, MNCut: Multi-scale normalized cuts-based segmentation (a) MSEs and bound under the biased estimator assumption; (b) variances and bound under the unbiased estimator assumption.



(a) (b)

Fig. 7 Bounds for hard image segmentation (real-world image, namely a mammogram). (a) MSEs and bound for biased estimator assumption (b) variances and bound for unbiased estimator assumption.



(a) (b)

Fig. 8 Bounds for hybrid image segmentation (a synthetic image), where both fuzzy pixels and hard pixels exist in the image (a) MSEs and bound for biased estimator assumption (b) variances and bound for unbiased estimator assumption.

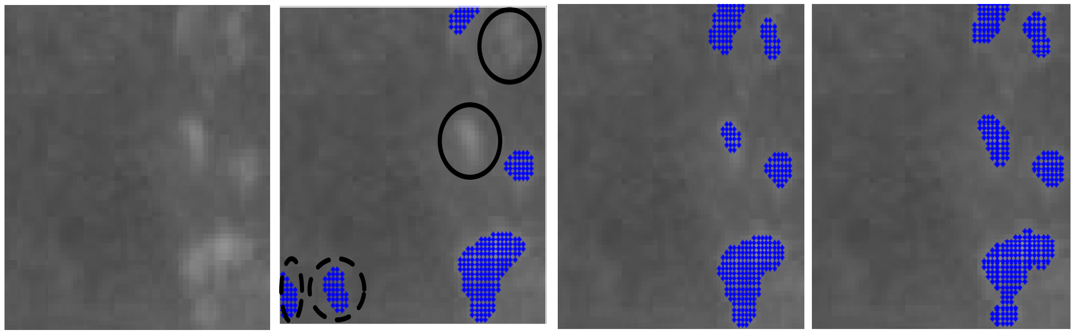
A HVS-Driven Image Segmentation Framework Using Local Segmentation Performance Measure

Markov random field (MRF) models have been used to represent contextual information in many pixel-based segmentation problems, because they can be employed to characterize the spatial dependency or spatial distribution. A statistical method, namely the MAP approach, is often used during MRF-based image segmentation, which has been investigated comprehensively. The MAP-MRF method maximizes an objective function consisting of the *a priori* density in terms of the Gibbs distribution and the conditional probability density function (PDF for continuous data, and probability mass function, PMF, for discrete data) of the observed image data given the distribution of the segmented region, in which some image features are often embedded. However, some strong assumptions and inaccurate estimates of the conditional PMF corresponding to intensity values of single pixels limit its performance and application.

Moreover, many existing segmentation algorithms have been developed based on the information provided by the image data themselves and neglect the fact that a human is usually the ultimate evaluator. That is, they do not consider the effect of the HVS on object interpretation and extraction. As a result, many algorithms perform unsatisfactorily from a human vision point of view.

In an attempt to address the above two problems, we presented a novel image segmentation framework. The framework was based on a "soft" objective function which considered the effect of the segmentation result for a single pixel on the segmentation performance in local regions. A specific performance measure, the probability of successful detection, was used in this work to show the efficiency and utility of this framework. Moreover, a contrast sensitivity function (CSF), as an object feature enhancer, was employed for further improving the segmentation performance, which made the

segmentation procedure HVS-driven.



(a) (b) (c) (d)

Fig. 9 (a) Original mammogram with micro-calcifications; (b) segmentation result with MAP-MRF; (c) segmentation result with the presented algorithm without CSF enhancement; (d) segmentation result of the presented algorithms after CSF enhancement. The detected positives are marked with dots, the false positives and missed lesions are pointed out by dashed circles and solid circles, respectively.

Voice Activity Detection with Stochastic Resonance

In this work, stochastic resonance was applied to speech signal processing. In particular, we presented a method to improve detection performance of a suboptimal voice activity detector without changing it. In our experiments, we used Sohn and Sung's voice activity detector as our reference detector. This detector was designed by using the Generalized Likelihood Ratio Test (GLRT) method under the assumptions that speech and noise signals are Gaussian random processes that are independent of each other and the Discrete Fourier Transform (DFT) coefficients of each process are asymptotically independent Gaussian random variables. However, recent studies have shown that Laplacian and Gamma distributions more accurately represent DFT coefficients of clean speech and noise signals. Therefore, Sohn and Sung's voice activity detector is suboptimal because of its underlying design assumptions and can be improved. In this study, in order to improve the detection performance, the input signal of the detector was preprocessed using the bistable SR system used as a SR filter. Optimum SR filter parameters were obtained by using the deflection coefficient. Due to the high complexity of the signal of interest, the coefficients were found in an iterative manner. Experiments conducted on different input signals and training data sets showed that it is possible to get optimum parameters, even when only 20% of the input signal is used as training data, if it has enough information about the distribution of input signal. The detector performance of the system before and after the SR filter was compared using the Receiver Operating Curves (ROC). From the ROCs, we observe that our method improved detection performance up to 17.5% for lower false alarm rates and up to 4.5% for higher false alarm rates. Based on the simulation results, our method is an efficient method to improve detection performance of suboptimal voice activity detector.

Performance Analysis of Sparse Signal Detection and Classification with Compressive Measurements

Compressive Sensing (CS) enables the recovery of sparse or compressible signals from a relatively small number of randomized projections on original measurements compared to that with the original length samples. Although most of the recent CS literature has focused on sparse signal recovery, there are signal processing applications where complete signal recovery is not necessary. Instead we might be only interested in solving inference (detection, classification or estimation of certain parameters) problems. Solving inference problems with compressive measurements has been given some attention in the recent CS literature in different contexts.

In this work, we considered the detection and classification of sparse as well as non-sparse stochastic signals with compressive measurements. We derived the performance limits of the optimal detector and bounds on probability of error of the optimal classification rule when the signals to be detected/classified are random and not necessarily sparse, and detection/classification is performed with M ($M < N$, N is the signal dimension) length compressive measurements. Specifically we showed that, *Kullback-Leibler (KL)* and *Chernoff* distances, which are important distance measures in evaluating performance of detection/classification, are distorted by a factor of *M/N* with *M*-length compressive measurements compared to that with *N*-length original measurements. For sparse signal detection with K non-zero elements with unknown supports, we derived approximate performance measures when certain prior information on the support sets of sparse signals is available.

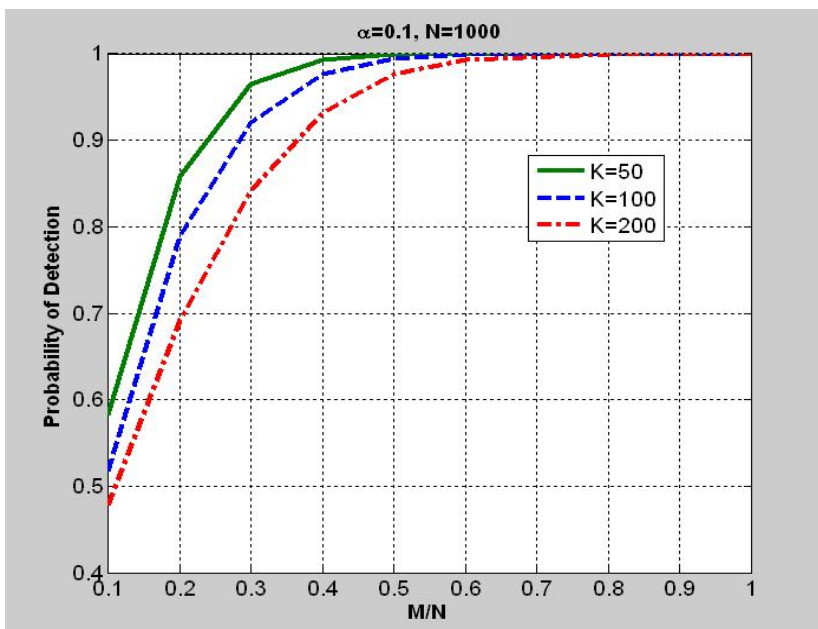


Fig. 10 Probability of detection Vs. *M/N* in sparse signal detection with a fixed signal-to-noise-ratio (SNR); probability of false alarm $\alpha = 0.1$, *N*=1000

Performance Bounds for Sparse Support Recovery with Quantized Compressive Measurements

Sparse support recovery is concerned with finding the locations of the non-zero elements of a sparse signal. The problem of sparsity pattern recovery arises in a wide variety of areas including source localization, sparse approximation, subset selection in linear regression, and signal denoising. This problem has been addressed by many authors in the last few decades in different contexts. With the recently introduced sparse signal acquisition scheme via random projections, named CS, the sparse support recovery problem has received much attention in the context of random dictionaries.

In this work, the problem of support recovery of sparse signals with quantized compressive measurements is considered. Although most of the CS literature has focused on sparse signal recovery from real valued compressive measurements, it is important to consider quantization of compressive measurements since in practice, measurements are quantized before transmission or storage. To that end, we found the sufficient conditions which ensure the reliable recovery of the sparsity pattern of a sparse signal from quantized compressive measurements in the presence of noise. More specifically, we found the relationships among the parameters, the signal dimension, sparsity index, number of compressive measurements, number of bits used for quantization, and the signal to noise ratio which ensure the asymptotic reliable recovery of the support of sparse signals with the Maximum Likelihood (ML) decoder when the entries of the measurement matrix are drawn from a Gaussian ensemble.

A New Approach to Fourier Synthesis with Application to Neural Encoding and Speech Classification

It has been shown that a positive signal can be alternatively represented by a Fourier expansion using only “on-off” unit amplitudes. This mimics what the ear does in the cochlea, whereby the hair cells either fire or do not fire. This representation is a new one and may explain how the brain accomplishes neural coding, a holy grail in cognitive science research.

A Poisson Spectral Representation for Random Process Modeling

Another result is by modeling the neural firings by a nonhomogenous Poisson process a new spectral representation is possible. This spectral representation has already been used to synthesis random processes with an arbitrary power spectral density and first-order probability density function, which has solved a long standing problem. Additionally, this Poisson representation may lead to a two-dimensional “place-rate” neural encoding model to describe how the ear encodes sounds. Finally, with the new representation we have been able to show that noise can enhance the neural firings, which now indicates how stochastic resonance accomplishes its enhancement of signal recognition.

Encoding of Sound in the Human Ear

We have investigated the encoding of sound in the human ear. Neural encoding, i.e., the means by which the ear is able to convey information to the brain by using only a sequence of temporal neural spikes, can be explained by a new signal representation. It is shown how a signal may be neurally encoded, and then how to use that model to explain the enhancement of a low level signal by the addition of noise. The latter is

generally known as stochastic resonance. In particular, the results indicate how a positive deterministic signal can be perfectly represented using a sequence of nonuniformly spaced impulses, all with the same strength. The latter is in contrast to the usual linear systems representation of a signal as an integral of varying strength Dirac impulses. The mathematical model, interestingly, is equivalent to the very simple ``integrate and fire'' model used to describe the action of a neuron. Hence, it is conjectured that results may help to explain the signal processing operation of the neuron and how it is able to transfer signal information to the brain. Many other models exist for this neural encoding but it is important to note that the one proposed is the simplest one that is directly motivated by the physics of the ear.

5. Personnel Supported

- Prof. Pramod K. Varshney (PI)
- Dr. Steven Kay
- Dr. Makan Fardad (Assistant Professor)
- Dr. Hao Chen (Research Assistant Professor)
- Dr. Thakshila Wimalajeewa Wewelwala (Post-Doctoral Research Associate)
- Renbin Peng (Ph.D. student)
- Arun Subramanian (Ph.D. student)
- Yujiao Zheng (Ph.D. student)
- Himanshu Neema (M.S. student)

6. Publications

Journal Articles and Conference Proceedings

[1] H. Chen, P. K. Varshney, J. H. Michels and S. M. Kay, "Noise enhanced nonparametric detection," *IEEE Transactions on Information Theory*, vol. 55, no. 2, pp. 499–506, 2009.

[2] R. Peng, H. Chen, and P. K. Varshney, "Noise-enhanced detection of micro-calcifications in digital mammograms," *IEEE Journal of Selected Topic in Signal Processing*, vol.3, no.1, pages 62-73, Feb. 2009.

[3] H. Chen and P. K. Varshney, "Performance limit for distributed estimation systems with identical one-bit quantizers," *IEEE Transactions on Signal Processing*, vol. 58, no. 1, pp. 466–471, Jan. 2010.

[4] R. Peng, H. Chen, and P. K. Varshney, "Noise-refined image enhancement using multi-objective optimization," in *Proc. of IEEE 44th Annual Conference on Information Sciences and Systems (CISS)*, Princeton, NJ, Mar.17-19, 2010

[5] H. Chen and P. K. Varshney, "Nonparametric quantizers for distributed estimation," *IEEE Trans. Signal Processing.*, vol 58, no 7, pp. 3777-3787, July 2010.

[6] S. Kay, "A New Approach to Fourier Synthesis with Application to Neural Encoding and Speech Classification", *IEEE Signal Processing Letters*, Oct. 2010

[7] R. Peng, and P. K. Varshney, "A human visual system-driven image segmentation framework using a local segmentation performance measure," *IEEE Western NY Image Processing Workshop*, Rochester, NY, Nov. 5, 2010

[8] T.Wimalajeewa, H. Chen and P. K. Varshney, "Performance Analysis of Stochastic Signal Detection with Compressive Measurements", 44th *Annual Asilomar Conf. on Signals, Systems and Computers*, Pacific Grove, CA, Nov 2010
[9] M. Gagrani, P. Sharma, S. Iyengar, V. S. S. Nadendla, A. Vempaty, H. Chen, and P. Varshney, "On noise enhanced distributed inference in the presence of byzantines," in Proceedings of Allerton-2011, Urbana, IL, 2011.
[10] T. Wimalajeewa and P. K. Varshney, "Performance Bounds for Sparsity Pattern Recovery with Quantized Noisy Random Projections", *IEEE Journal of Selected Topics in Signal Processing, Special Issue on Robust Measures and Tests Using Sparse Data for Detection and Estimation*, pp. 43-57, Feb 2012
[11] S. Kar, H. Chen and P. K. Varshney, "Optimal Identical Binary Quantizer Design for Distributed Estimation," To appear in *IEEE Trans. on Signal Processing*
[12] T. Wimalajeewa, H. Chen and P. K. Varshney, "Performance Limits of Compressive Sensing-Based Signal Classification", *IEEE Trans. Signal Processing.*, revised, Nov 2011, (submitted, June 2011)
[13] S. Kay, "A Poisson Spectral Representation for Random Process Modeling", *IEEE Trans. On Signal Processing,* submitted
[14] S. Kay, "A New Signal Representation and its Application to Auditory Neural Encoding and Signal Enhancement via Noise Addition", *IEEE Trans. On Signal Processing,* submitted
[15] Satish G. Iyengar, Ruixin Niu, and Pramod K. Varshney, "Fusing Dependent Decisions for Hypothesis Testing with Heterogeneous Sensors," IEEE Transactions on Signal Processing (submitted)

Theses and Dissertations

[1] Ilker Ozcelik, "Voice Activity Detection using Stochastic Resonance", *MS Thesis* (Advisor: Prof. Pramod K. Varshney, Co-advised with H. Chen), Syracuse University, June 2010.
[2] Renbin Peng, *Noise Enhanced and Human Visual System-Driven Image Processing Algorithms and Performance Limits.* (Advisor: Prof. Pramod K. Varshney), Syracuse University, 2011

7. News Articles

- P. K. Varshney, "Adding noise can improve accuracy of digital mammograms," *RT Image Magazine*, Feb. 1, 2010
- H. Chen, "Constructive Role of Noise in Signal Processing", SPIE Newsroom.
- Press coverage of work on digital mammography, Radio FM 88 and interview with newspaper L.A. Times.
- Digital mammography work appeared in ACM Tech News on Feb. 3, 2010.

8. Interactions/Transitions

Invited talks:

- P.K. Varshney, "Noise Enhanced Signal and Image Processing", AFRL, WP Air Force Base, July 2009

- H. Chen, “Noise Enhanced Signal Detection and Estimation,” *Mitsubishi Electric Research Laboratories,* Dec. 17, 2009.

Interactions:

- There have been many interactions with industries that design and manufacture mammography machines with regard to our work on image enhancement based on SR.
- Lectures at Lockheed Martin in Syracuse and SRC that included discussion on SR.
- There has been interaction with Dr. Andy Noga of AFRL Information Directorate in the area of compressive sensing. In addition, there has been interaction with Don Leskiw of Leskiw Associates that resulted in an STTR Phase I award.

Collaborations:

- There has been an ongoing collaboration with Dr. Ramdas Kumaresan, University of Rhode Island with regards to the biological implications of hearing on signal processing.

9. New Discoveries/Inventions/Patents

- H. Chen, J. Michels and P.K. Varshney, Optimized Stochastic Resonance Method for Signal Detection and Image Processing, US 7,668,699 B2, Issued Feb. 23, 2010.
- A child application covering the mammography application is in progress.

10. Honors/Awards

- Renbin Peng won the Nunan Award in a college-wide poster presentation competition at Syracuse University.
- 2010 University of Rhode Island Foundation Scholarly Excellence Award
- Pramod Varshney is the recipient of the IEEE 2012 Judith Resnik Award.